Calibration and Verification of Three Computer Seasonal Forecast Models

John A. Dutton

Richard P. James

Jeremy D. Ross

Prescient Weather Ltd

World Climate Service

CFSv2 Evaluation Workshop 30 April – 1 May 2012 Riverdale, MD









If you knew then, what we knew then

www.worldclimateservice.com



Logged in as 'jad'

Logout

Change Password

If you knew then what we knew then ...

Home Forecasts Climate Analysis Tools Free Climate Tools About Us Contact

Region selection





Model selection

Model Variable Forecast



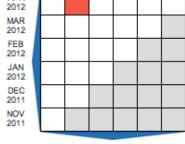
Climatology selection (note)

1982-2009 2000-2009

Month selection



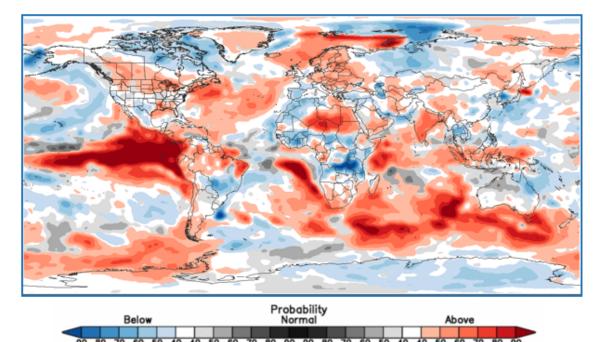
Reset



CFSv2 Temperature Probability 2000-2009 Climatology Forecast made April 2012 for June 2012

Click on map to:





Download as:

PDF

GeoTiff

KMZ



Logged in as 'jad'

Logout

Change Password

If you knew then what we knew then ...

Home **Climate Analysis Tools Free Climate Tools About Us** Contact **Forecasts**

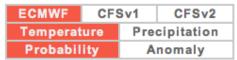
Region selection





Model selection

Model Variable Forecast



Climatology selection (note)

1981-2010 2001-2010

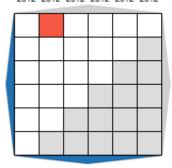
Month selection



2012 MAR 2012 Forecast made



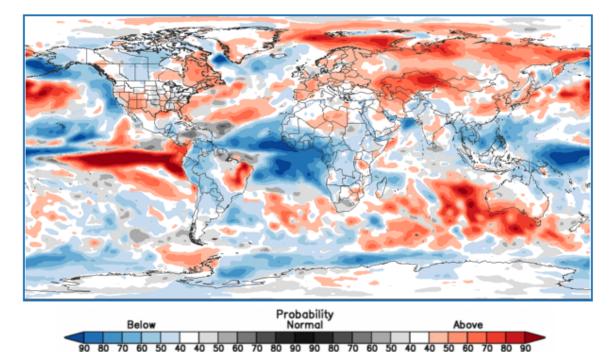
2011



ECMWF Temperature Probability 2001-2010 Climatology Forecast made April 2012 for June 2012

Click on map to:

Zoom In



Download as: PDF GeoTiff KMZ

Topics for Today

- Seasonal Forecasts—Comparison of Models
- Some Troubling Issues
- Multi-scale Ensemble Forecasts

Acknowledgment

This research was supported in part by NOAA with a Small Business Innovation (SBIR) Phase One Contract



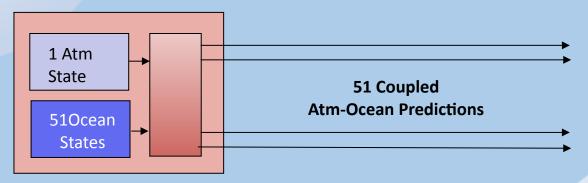
Goal of Seasonal Prediction

Provide users with reliable probabilities of deviations from average atmospheric and oceanic conditions in the months or seasons ahead so that they can manage risk and take advantage of opportunity.



Two seasonal forecast strategies

ECMWF SPS v4





NCEP CFS v2

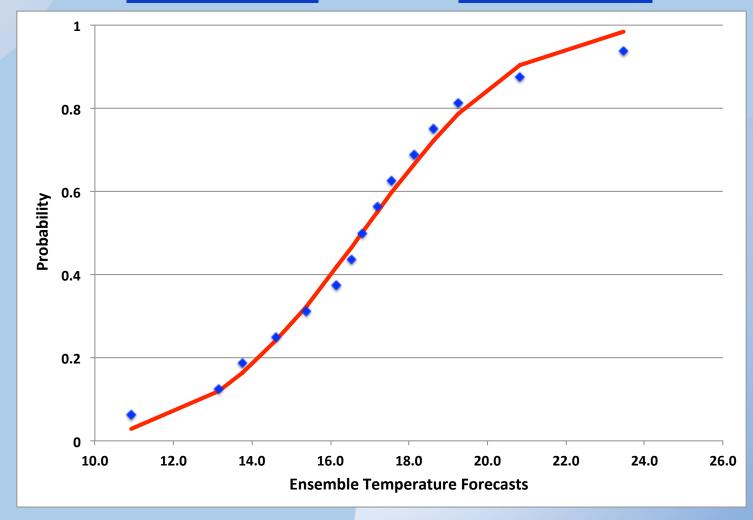




An Ensemble Forecast

=

A Forecast of Probability

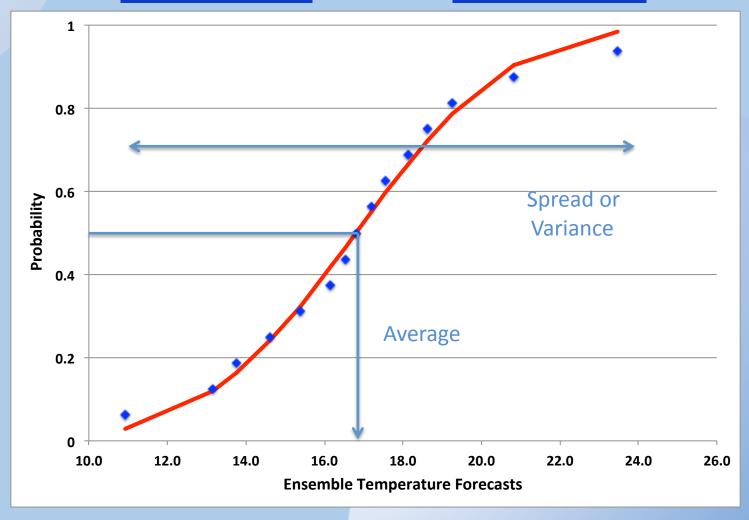




An Ensemble Forecast

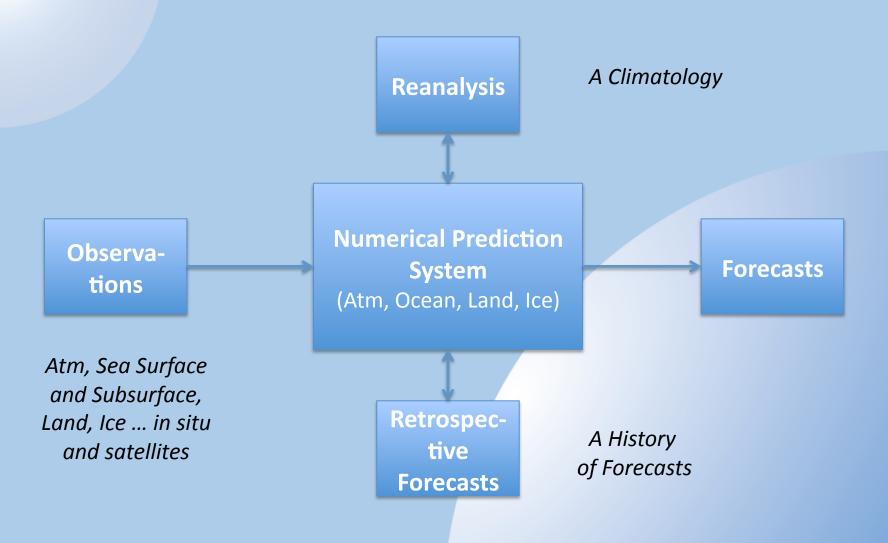
=

A Forecast of **Probability**



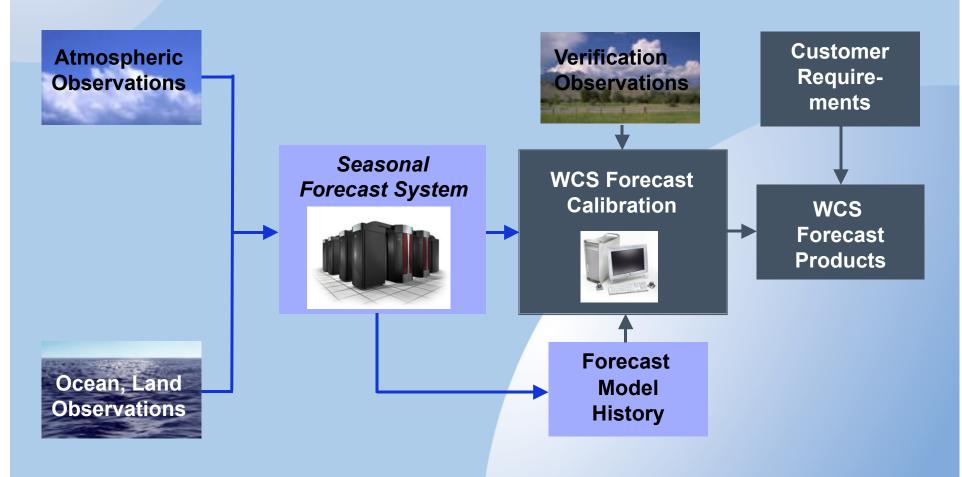


Components of a Seasonal Prediction System





The WCS Seasonal Prediction System





A Critical Assumption of Seasonal Prediction

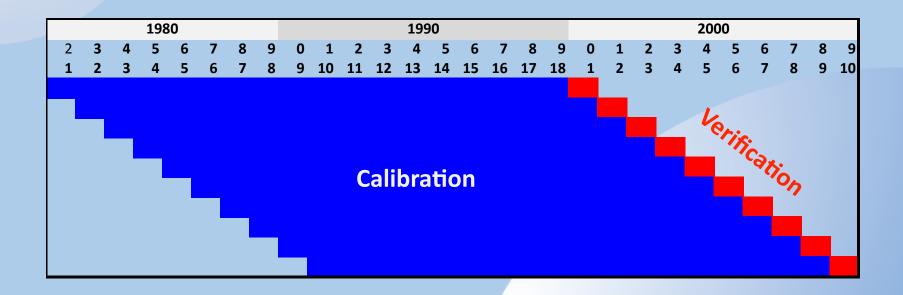
Past errors are a prolog to future errors and can be used to improve future forecasts.

The reanalysis, the retrospective forecasts, and the operational forecasts are equally important components of a forecast system.

They should be statistically stationary in order to calibrate the forecasts.



Seasonal Forecast Calibration and Verification





Observations

Comparing Forecasts To Observations

Forecasts

	Α	N	В	
A	а	b	С	na
N	d	е	f	nn
В	g	h	i	nb
	fa	fn	fb	1

Success Ratio Sa=a/(a+d+g)=a/fa

Fraction of events predicted

correctly

Fraction Correct Fa=a/(a+b+c)=a/na

Fraction of correct forecasts



Forecast Skill Summaries

$$na Fa + nn Fn + nb Fb = F$$

$$fa Sa + fn Sn + fb Sb = S$$

$$F_p = S_p = 1$$

Random Forecasts
$$F_r = S_r = 1/3$$

$$F_r = S_r = 1/3$$

Improvement Ratios
$$(F - F_r) / F_r = (S - S_r) / S_r$$

Fraction Correct 2000-2009 October->DJF Variance Scaling

	Below	Normal	Above	All	Below	Normal	Above	All
		North A	merica		Europe			
CFSv2	0.45	0.38	0.45	0.43	0.43	0.46	0.47	0.46
ECMWFv4	0.37	0.39	0.46	0.41	0.26	0.37	0.36	0.34
Multi-model	0.46	0.42	0.47	0.46	0.39	0.41	0.43	0.42
		Glo	bal		Tropical Pacific			
CFSv2	0.45	0.39	0.52	0.48	0.74	0.32	0.45	0.48
ECMWFv4	0.4	0.38	0.53	0.45	0.82	0.44	0.7	0.62
Multi-model	0.49	0.41	0.54	0.5	0.83	0.41	0.59	0.56



Fraction Correct 2000-2009 April->JJA Variance Scaling

	Below	Normal	Above	All	Below	Normal	Above	All
		North A	merica		Europe			
CFSv2	0.39	0.43	0.42	0.42	0.25	0.40	0.47	0.43
ECMWFv4	0.42	0.43	0.42	0.42	0.24	0.41	0.48	0.43
Multi-model	0.41	0.44	0.43	0.43	0.34	0.41	0.48	0.46
		Glo	bal		Tropical Pacific			
CFSv2	0.30	0.40	0.51	0.44	0.67	0.35	0.48	0.52
ECMWFv4	0.30	0.40	0.52	0.43	0.61	0.42	0.61	0.54
Multi-model	0.32	0.42	0.52	0.46	0.68	0.45	0.56	0.55



Success Ratio 2000-2009 October->DJF Variance Scaling

	Below	Normal	Above	All	Below	Normal	Above	All
		North A	merica		Europe			
CFSv2	0.39	0.20	0.67	0.43	0.29	0.31	0.70	0.46
ECMWFv4	0.46	0.27	0.49	0.41	0.20	0.25	0.51	0.34
Multi-model	0.39	0.26	0.68	0.46	0.15	0.29	0.73	0.42
		Glo	bal		Tropical Pacific			
CFSv2	0.41	0.24	0.69	0.48	0.33	0.09	0.94	0.48
ECMWFv4	0.37	0.34	0.58	0.45	0.43	0.57	0.81	0.62
Multi-model	0.37	0.33	0.70	0.50	0.33	0.43	0.88	0.56



Success Ratio 2000-2009 April -> JJA Variance Scaling

	Below	Normal	Above	All	Below	Normal	Above	All
		North A	merica		Europe			
CFSv2	0.27	0.25	0.69	0.42	0.13	0.23	0.71	0.43
ECMWFv4	0.33	0.25	0.66	0.42	0.18	0.26	0.67	0.43
Multi-model	0.25	0.31	0.68	0.43	0.09	0.24	0.78	0.46
		Glo	bal		Tropical Pacific			
CFSv2	0.29	0.25	0.65	0.44	0.51	0.03	0.97	0.52
ECMWFv4	0.35	0.38	0.51	0.43	0.53	0.41	0.67	0.54
Multi-model	0.27	0.35	0.62	0.46	0.43	0.30	0.88	0.55



Relative Performance as Best Model DJF, JJA — NA, EU, GL, TP — 2000-2009

	Fraction Correct (%)	Success Ratio (%)	Both (%)
CFSv2	12.5	21	17
ECMWFv4	12.5	50	31
Multi- Model	75	29	52



Return on Hypothetical Plain Vanilla Options

An option on *Above, Normal,* or *Below* costs \$*P* and pays \$3*P* for the event that occurs.

For *F* the fraction of correct forecasts, the rate of return is

$$R = (3 FP - P)/P$$

= $(3 F - 1)$
= $(F - F_r)/F_r$

Multiply by 100 for per cent.

Fraction Correct	Virtual Return (per cent)
0.333	0
0.416	25
0.5	50
0.583	75
0.666	100



Average Fraction Correct and **Average Hypothetical Return**

O -> DJF, A->JJA — 2000-2009

WCS Multi-Model

	Global	North America	Europe
Fraction Correct	0.48	0.44	0.44
Return (%)	44	32	32



Fraction Correct WCS Multi-Model October -> DJF, 2000-2009 Probability Threshold 50 percent

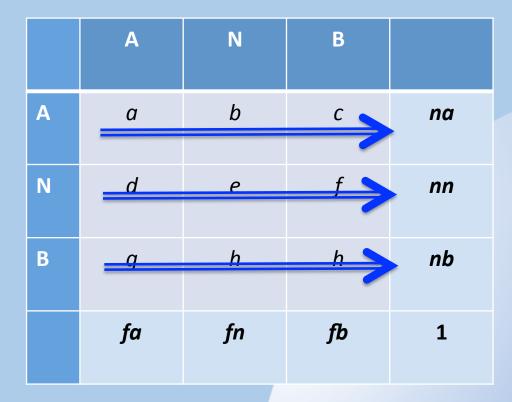
	Below	Normal	Above	All
GL	59	48	59	57
NA	58	48	53	54
EU	26	39	56	53
TP	91	42	62	59



Comparing Forecasts To Observations

Number of Observations

Number of Forecasts

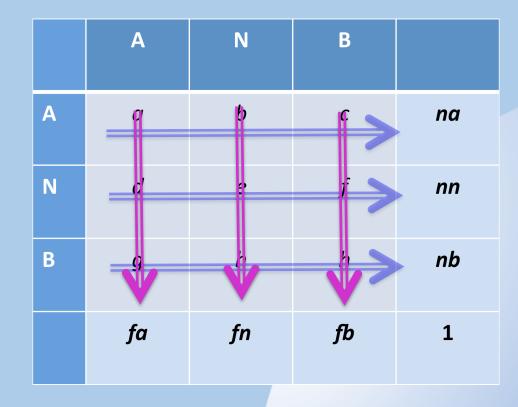




Comparing Forecasts To Observations

Number of Observations

Number of Forecasts



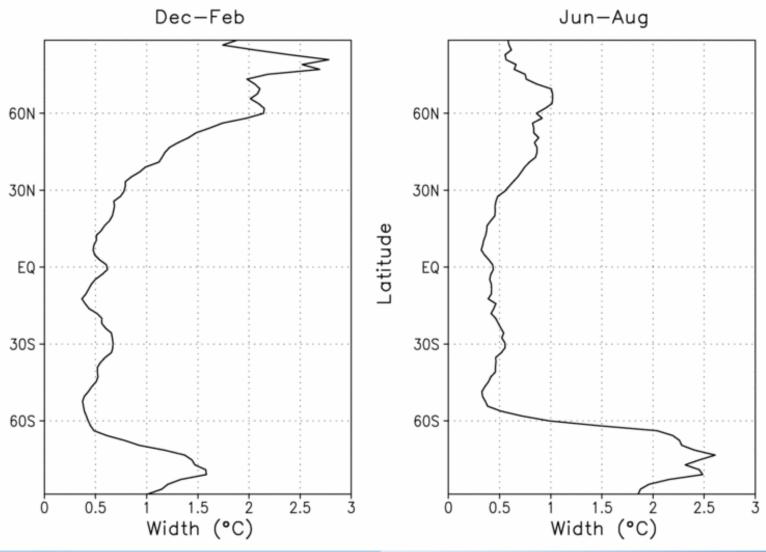


WCS Multi-Model Ensemble Forecasts for 2000-2009

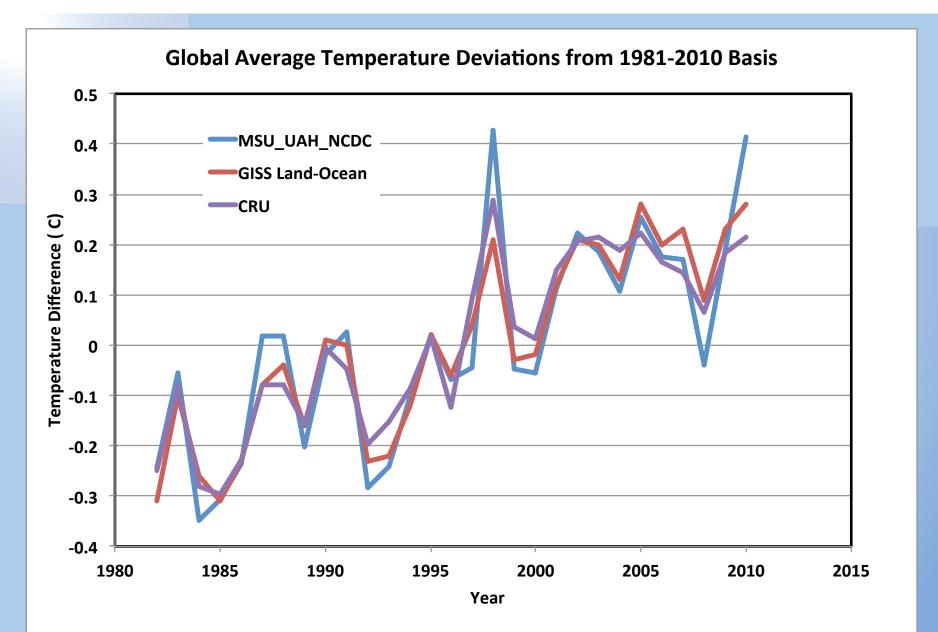
	0	ctober->D)JF		April ->JJ	4
	Below	Normal	Above	Below	Normal	Above
GL Forecasts (percent)	20	25	55	18	28	54
GL Obs (percent)	26	31	43	21	33	46
Ratio	0.76	0.81	1.28	0.85	0.84	1.18
NA Forecasts	25	21	55	18	25	57
NA Obs	29	33	38	29	34	36
Ratio	0.84	0.63	1.44	0.62	0.72	1.57
EU Forecasts	10	23	66	5	21	75
EU Obs	28	33	40	19	35	46
Ratio	0.38	0.70	1.68	0.25	0.59	1.63
AU Forecasts (JJA DJF)	19	34	47	15	27	58
AU Obs (JJA DJF)	21	36	43	25	34	42
Ratio	0.92	0.95	1.08	0.62	0.81	1.38
TP Forecasts	12	33	54	17	23	60
TP Obs	32	32	36	27	35	38
Ratio	0.39	1.05	1.49	0.64	0.66	1.58



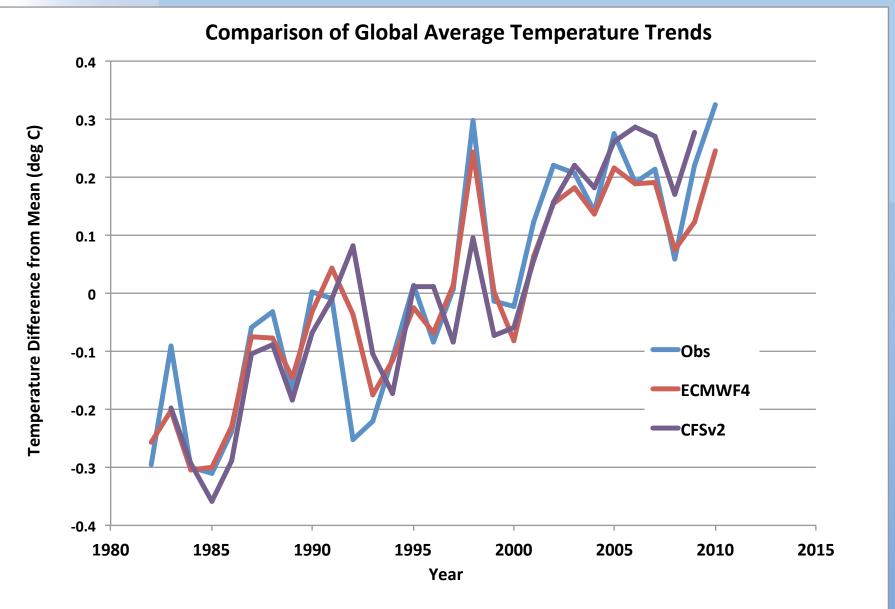
Width of Near-Normal Temperature Tercile (°C) Zonal Average 180 °W - 180 °E NCEPGR-2



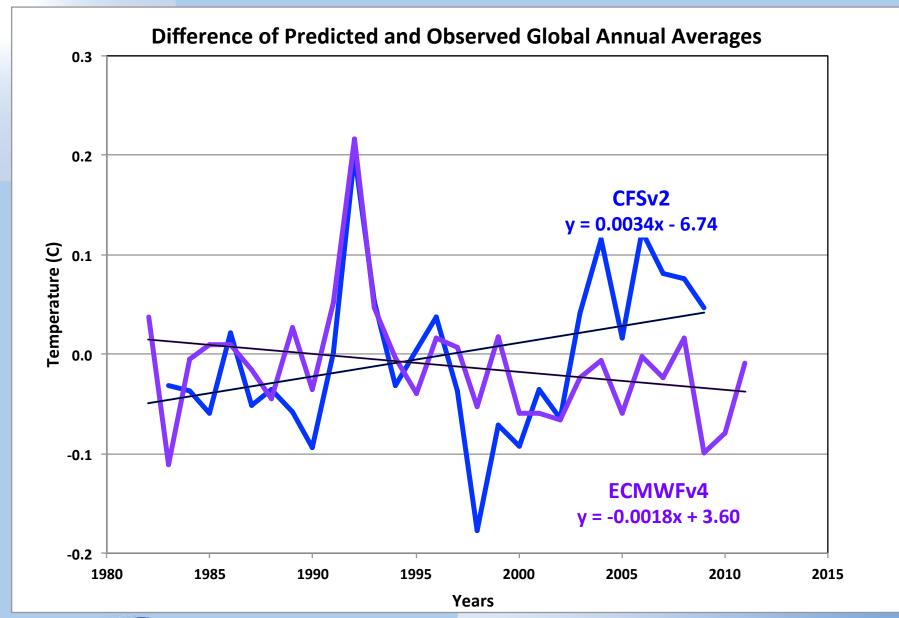




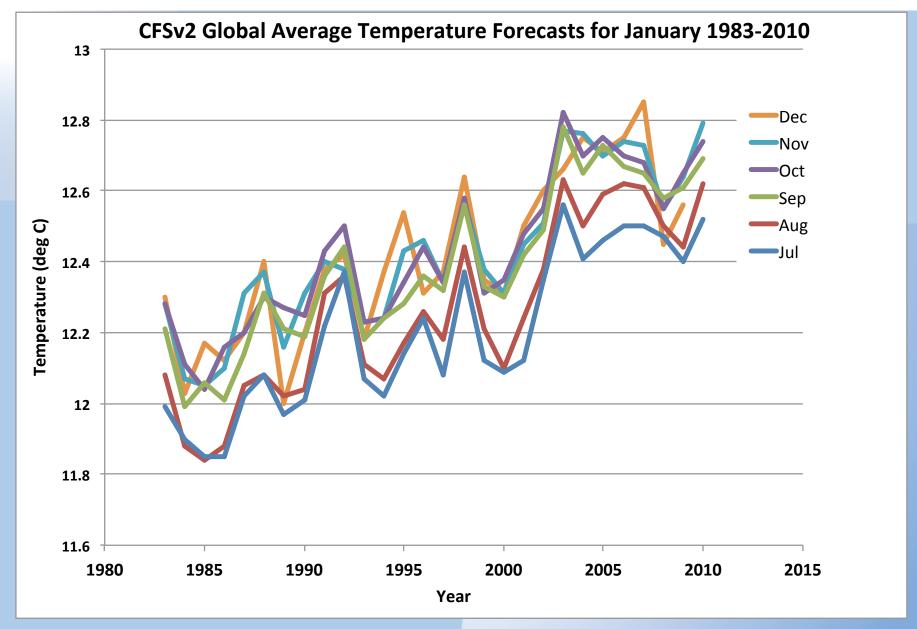




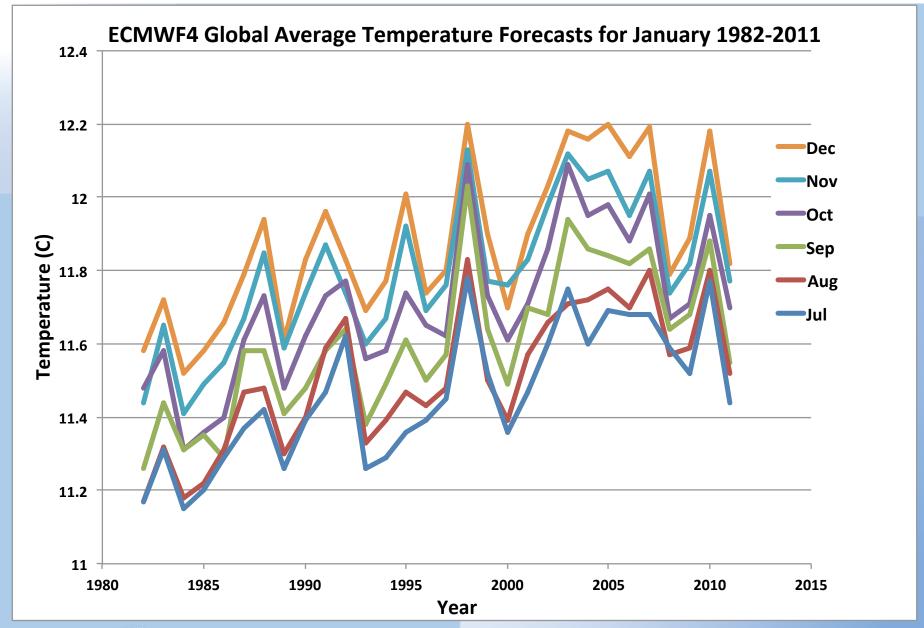






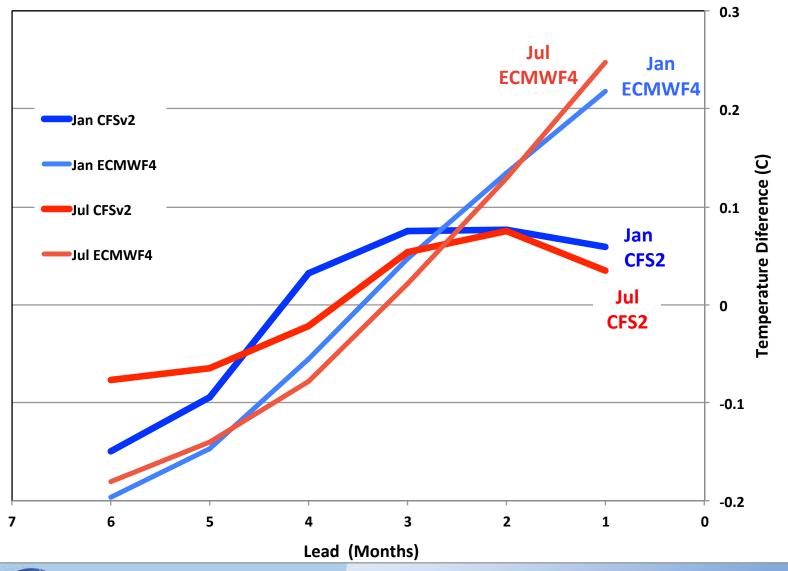














It seems that CFSv2 is warming more rapidly than the observations; ECMWF is not warming as fast.

A first try at reconciling trends in the same way we reconcile averages by removing bias was not successful.

The standard statistical advice is to separate long-term trends and short-term variations and treat them independently.

Perhaps we should follow that advice.



WCS Multi-scale Ensemble Prediction System

The reliability of forecasts can be improved by averaging over increasing periods as the lead time increases ...

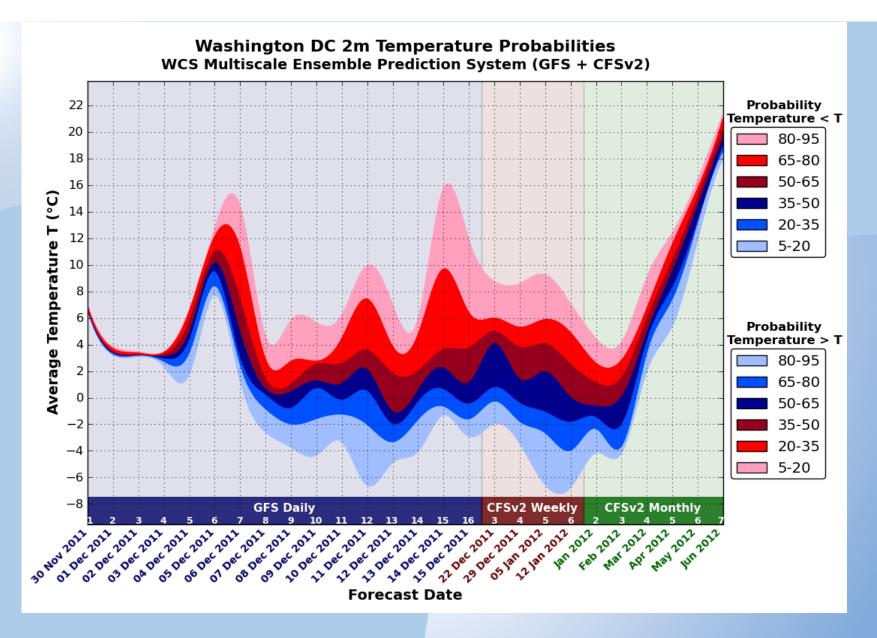
a day for forecasts days ahead

a week for forecasts weeks ahead

a season for forecasts seasons ahead

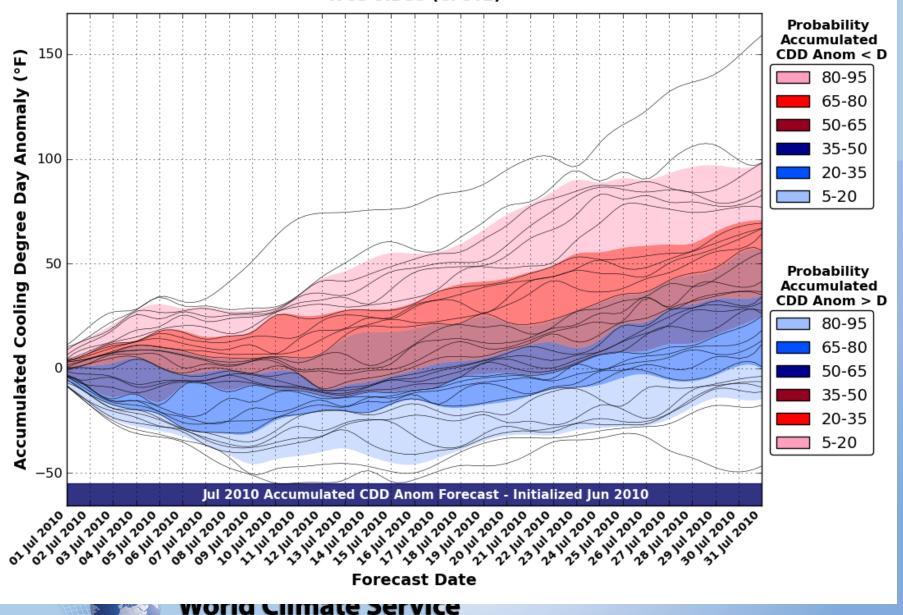
Multi-scale probabilistic forecasts can be constructed by using increasing average times as lead times increase







Washington DC Cooling Degree Day Anomaly Probabilities WCS SIDSS (CFSv2)





Summary

- The calibrated seasonal probability forecasts demonstrate sufficient skill to be of value in the energy and other industries for mitigation of risk and identification of opportunity;
- The WCS multi-model is somewhat better on average than either CFSv2 and ECMWFv4 used alone and offers hypothetical rates of return of greater than 30 per cent.
- Forecast performance will likely be improved with improved management of the effects of climate trends; perhaps we should rethink our modeling strategy.
- New methods of presenting probabilities will assist users to make more effective decisions.





Transition to Energy Variables

Energy impact variables are often non-linear functions of atmospheric variables

Heating Degree Days = $Max[T_0-T, 0]$

Available Wind Energy $\approx w(V) V^3$

Probability distributions for these variables must be computed from the six-hourly data of the seasonal forecast ensembles and then examined or averaged as required for decision support.

